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Dynamic and Feed-forward Neural Networks for Load Frequency Control of Two-Area Power Systems

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ABSTRACT:
This work involves the application of multilayer feed-forward neural network and dynamic neural network for the load frequency control of two-area power systems. The control schemes adopt a formulation for the area control error which always guarantee zero steady state time error and inadvertent interchange. The controller takes into account the control dead bands and generation rate constraints. The input signals to the static neural net models are turbine output, hydraulic amplifier output, change in frequency variations and load perturbations. The output signal is taken as the reference power setting. The input signal to the dynamic neural network models are area control error (ACE). The outputs are the control signals for two area load frequency control. Adaptation is based on adjusting the parameters of each area for load frequency control. This is done by minimizing the cost functional of load frequency deviations. It is observed that both multilayer feed-forward neural network and dynamic neural network load frequency controls are giving better dynamic and steady state characteristics over the operating range compared to the conventional PI controller. Classical dynamic neural network models learn faster than multilayered feed-forward neural networks, it has less number of parameters than the multilayered feed-forward neural network model.

The effectiveness of the reported neural network methods for load frequency control of a two area system is established by comparing the results against those obtained with conventional PI controllers

KEYWORDS— *Two-Area Power systems, Multilayer Feed-forward Neural Network, Dynamic Neural Network, Load Frequency Control, Conventional PI Controller*

I. INTRODUCTION

1.1 Introduction:

As demand fluctuates from its normal operating value the state of the system changes. To maintain the system at normal operating state different types of controllers based on classical linear control theory has been developed in the past. Most load frequency controllers are primarily composed of an integral controller. The integrator gain is set to a level that compromises between fast transient recovery and low overshoot in the dynamic response of the overall system. This type of controller is slow and does not allow the designer to take into account possible non-linearity in the generator unit. In this work artificial neural network based load frequency control is presented so as to overcome these problems. In this work both multilayer feed forward neural network and dynamic neural networks are utilized for load frequency control of two area system. The inherent non-linearity in system components and synchronous machines have led to build a non-linear ANN controller with high efficiency of performance. There exist problems in the implementation of artificial neural networks (ANN), based control designs for load frequency control of a dynamical system due to a large parallel input vector consisting of a number of states or past samples of process data as discussed in this section. This ‘‘tapped delay line’’ approach has been proven successful, but it has the same drawbacks: the number of layers increases exponentially, and the parameters in Artificial Neural Network get larger values.

The above mentioned setbacks of artificial neural network based load frequency control with large network sizes; large training times, etc. can be minimized with Dynamic Neural Networks (DNN). Dynamic neural networks are simple standard neuron models with feedback elements from input, output and in between the weights of the neurons which are interconnected to form layers of neurons. This dynamic neural networks are trained to track any curve or function by comparing its response with desired response of the model and deviations in its response can be rectified by adjusting the weights of the dynamic neural networks using adjoint sensitivity analysis.

The nonlinear optimal load frequency control algorithm operates as an auto-trainer for dynamic neural network which generates the initial optimal feed forward control trajectories. Direct descent- curvature algorithm with some modifications has been used for optimal load frequency control computations. The overall system can be considered as an intelligent control system in the continuous adaptive structure. This work

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proposes a procedure for designing and analyzing adaptive schemes for load frequency control of two area power systems.

1.2 Outline Of Thesis:

The present work proposes a load frequency control method of two area systems with Multilayer feed forward Neural Network and Dynamic neural network models (DNNs). The operation and learning methods of conventional PI (proportional and integral control) and ANN (artificial neural network) based load frequency control methods respectively. Load frequency control of two area power system model and the values of layered weights, input weights and bias weights were obtained through proper training and results were given in this Thesis and Finally the types of DNN models and in-depth discussion regarding the Hopfield dynamic neural network models. The characteristics of the Hopfield dynamic neural networks and the outlines of the gradient analysis of Hopfield Dynamic neural networks. and simulation results and comparison between the Multilayer feed forward neural network and conventional PI controllers for load frequency control with Dynamic neural network models, conclusion and scope for the further work.

II. CONVENTIONAL LOAD FREQUENCY CONTROL OF TWO AREA SYSTEM

2.1 Introduction

In this Section, after discussing the block diagram of a two area system and the test system details, simulation results are presented. In a single area system mechanical power is produced by a turbine and delivered to a synchronous generator serving different users. The frequency at the output of the generator is mainly determined by the turbine steam flow .It also affected by changes in user power demands which appear, therefore, as electric “perturbations”. The electric load on the bus suddenly increases, the generator shaft slows down, and the frequency of the generator decreases. The control system immediately detect the load variation and command the steam admission valve to open more so that the turbine increases its mechanical power production ,counteracts the load increase and brings down the shaft speed and hence the generator frequency back to its nominal value.

Steam enters the turbine through a pipe that is partially obstructed by a steam admission valve. In a steady state the opening of the valve is determined by the position of the device called the speed changer. The reference valve, or set point, of the turbine power in steady state is called the reference power and is denoted by Pref. When the load on the bus suddenly changes, the shaft speed is modified, and a device called the speed regulator acts through the rigid rods to move the steam valve. Note a similar effect is produced by temporarily modifying the reference power (which justifies the name “speed changer”).In practice, both control schemes are used simultaneously. Amplifying stages (generally hydraulic) are introduced to magnify the outputs of the controllers and produce the forces necessary to actually move the steam valve.

The speed regulator is a proportional controller of gain 1/R .In conventional systems, an integral controller of gain KI sums the frequency fluctuations Δf and uses the result as a controller signal to the speed changer to raise or lower the reference power. By combining two control loops [Fig 2.1], we get a parallel PI (proportional –integral) controller capable of driving frequency fluctuations to zero whenever a step load perturbation is applied to the system .

Since most devices in power systems are nonlinear, one usually likes to linearize the plant and to think of different variables in terms of their fluctuations about given operating points. Nonlinearities are then modelled by making the parameters of the linearized system functions of the operating point. The resulting small signal models consist of linear operators having variable parameters whose values depend upon the state of the system. The last step in modelling consists of replacing all small signals by their Laplace transform and to represent the linearzed devices by transfer functions.

2.2 PI- LFC of Two Area System

A two area system consists of two single area systems connected through a power line called the tie line: each area feeds its user pool, and the tie line allows electric power to flow between the areas. Since both areas are tied together, a load perturbation in one area affects the output frequencies of both areas as well as the power flow on the tie line. For the same reason the control system of each area needs information about the transient situation in both areas in order to bring the local frequency back to its steady state value. Information about the local area is found in the output frequency fluctuation of that area. Information about the other area is found in the tie line power fluctuations. Therefore, the tie-line power is sensed, and the resulting tie-line power signal is fed back into both areas. This basic scheme is illustrated in Fig 2.1. The symbols and time constants used in the block diagram are

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KI, 1	Integrator gain of Area-1
KI, 2	Integrator gain of Area-2
KH, 1	Hydraulic amplifier gain of Area-1
KH, 2	Hydraulic amplifier gain of Area-2
KT, 1	Steam turbine gain of Area-1
KT, 2	Steam turbine gain of Area-2
KP, 1	Generator gain of Area-1
KP, 2	Generator gain of Area-2
TP, 1	Generator time constant of Area-1
TP, 2	Generator time constant of Area-2
B1	Frequency bias parameter of Area-1
B2	Frequency bias parameter of Area-2
R1	Regulation parameter of Area-1
R2	Regulation parameter of Area-2
TH, 1	Hydraulic amplifier time constant of Area-1
TH, 2	Hydraulic amplifier time constant of Area-2
TT, 1	Steam turbine time constant of Area-1
TT, 2	Steam turbine time constant of Area-2

In steady state each area output is nominal frequency. A load perturbation occurring in either area affects the frequencies in both areas as well as the tie-line power flow. With small signal approximation ,the fluctuation in power exchanged on the tie line, Δ P1,2(t),is proportional to the difference between the instantaneous shaft angle variations in both areas, $\Delta\theta$1 (t) and $\Delta\theta$2 (t).

These shaft angle variations are equal to 2Π times the integral of the corresponding frequency variations, Δf1 (t) and Δf2 (t).In the Laplace domain, the tie-line power deviation is

$$\Delta P1,2(s) = To(\Delta\theta 1 (s) - \Delta\theta 2 (s)) = 2\Pi\ To/s(\Delta f1 (s) - \Delta f2 (s) \qquad [2.1]$$

where To is a constant called the tie-line synchronizing coefficient. If the electric load increases in Area-2 (PE,2(s)>0) , then frequency in Area-2 decreases (F2(s)<0), and more power is transmitted from Area-1 to Area-2 (P1,2>0),in accordance with Eqn. 2.1.

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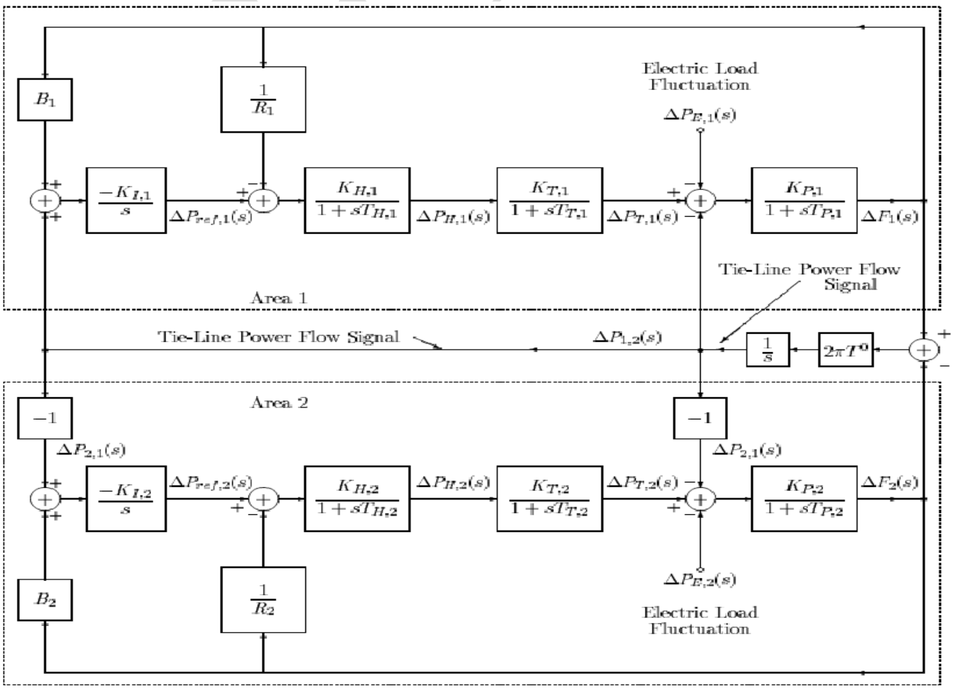

Fig. 2.1 small signal model of a two area system

In Area-1, this increase in tie-line power is perceived exactly the same way as an increase in power demand in Area-1. Hence in this model, P1,2(s) should be added to the same node as PE,1 and with the same sign (which is a minus sign).By symmetry,P2,1=-P1,2,the power going from Area-2 to Area-1,is added to the same node as PE,2,also with a minus sign.

In conventional systems, the turbine reference power of each area is set by an integral controller. Since a perturbation in either area affects the frequency in both areas and a perturbation in one area is perceived by the other through a change in tie line power, the controller of each area should take as input not only the local frequency variations, but also the tie line power variations. Since an integral controller has just one input, these two contributions (local frequency variations and tie line power variation) must be combined into a single signal that can be inputted in the controller. The easiest way of doing is to combine them linearly, i.e. the input of the integrator in Area-1 is P1, 2+B1 ΔF1, and the input of the integrator in Area-2 is P2,1+B2 ΔF2 (fig2.1) the coefficients B1,B2 are usually set to 1/KP+1/R .with the orders of magnitude ,B1= B2=0.425pu MW/Hz.

For any non negative integrator gains KI,1,KI,2 when a step load perturbation has occurred in Area-1 and /or in Area-2 ,and after transients have died out ,the frequency variations in both areas converge to zero, and so does the tie-line power. The plant state vector given by

$$X\,(nTS) = [\Delta f1\,(nTS) \quad \Delta\, f2\,(nTS) \quad \Delta\, P1,2(nTS)]\,T \qquad [2.2]$$

thus converges to steady state value equal to: X steady state = [0 0 0] T which shows that the steady state value of the frequency deviations in both the areas and the tie-line power variations from either the areas reaches zero for the system to be under normal operation state.

2.3 simulation results

The conventional load frequency control of two-area system presented in the previous section is simulated using SIMULINK. This section gives the data used and the simulation results. These are used for comparing the performance of artificial neural network and dynamic neural network based load frequency control. The simulink model of the conventional load frequency control of two area system is given in Fig. 2.2.The data used for the simulation of these systems is given in Table 2.1 and the percentage of the loads applied on two areas is given in this section. Simulations are carried out to analyze the frequency response in both the areas and the tie-line power deviations from either area by applying a small disturbance of 1% in area 1. This model is used as reference model for the remaining load frequency controllers for adjusting the parameters of the neural networks.

Table 2.1 Parameter values for two area system

KI,1 =.425	KI,2 =.425
KH,1 =0.1	KH,2 =0.1
TH,1=0.08	TH,2=0.08
KT,1 =1	KT,2 =1
TT,1 =0.3	TT,2 =0.3
KP,1 =1	KP,2 =1
TP,1 =19	TP,2 =19
B1=.425	B2 =.425
R1 =2.4	R2 =2.4

Percentage of load applied on area 1	1%
Percentage of load applied on area 1	0%
Synchronization coefficient TO	0.0707

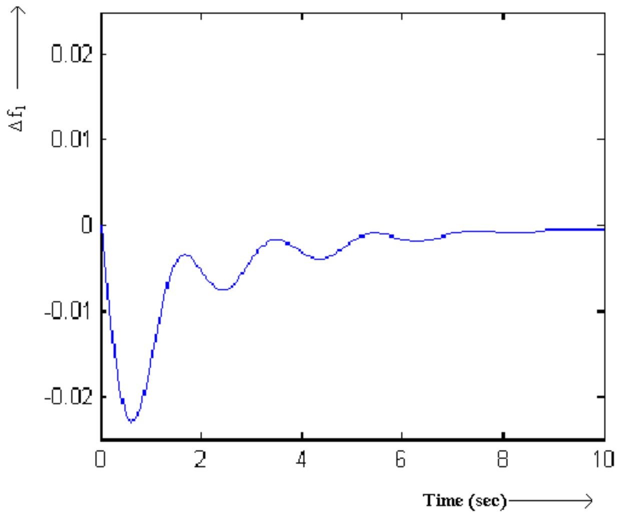

Fig 2.4(a).Frequency variations in area 1

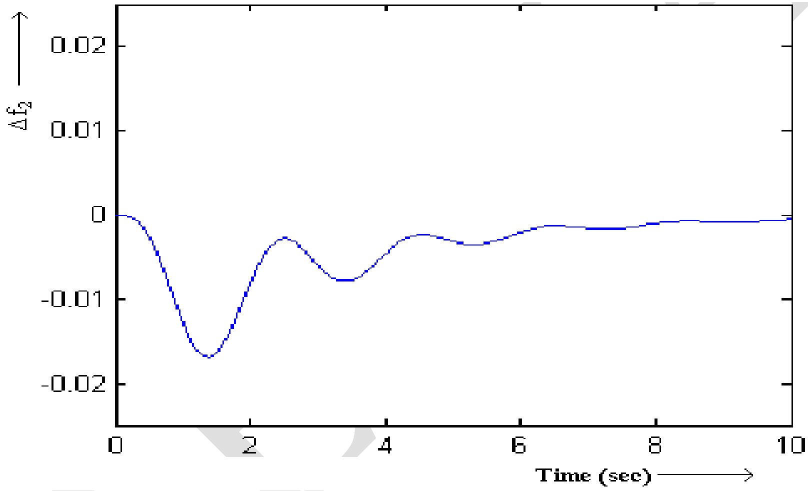

Fig 2.4(b).Frequency variations in area 2

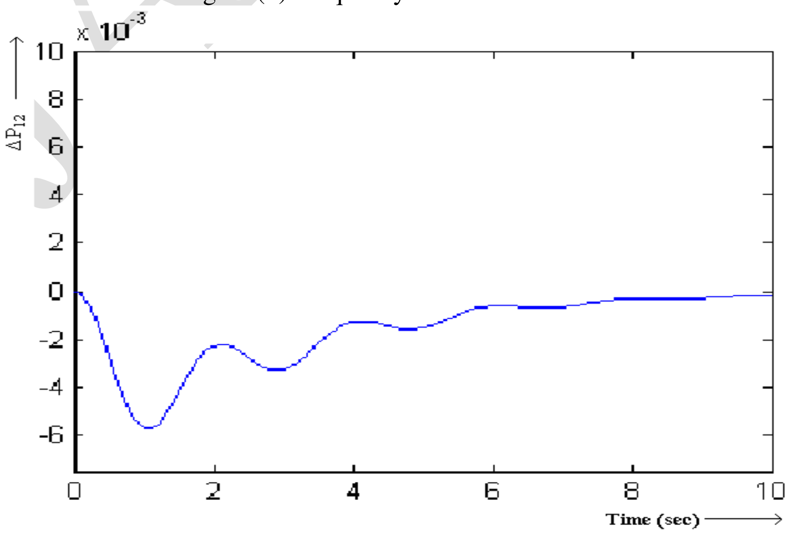

Fig 2.5 Tie-line power variations

From the plots, it is observed that the step load change of 1% disturbance in Area-1 resulted in 2.5% change of frequency from its nominal value in Area-1 and 1.75% change in Area-2. The steady state frequency value of zero is reached in approximately within 11 seconds. The tie-Line power variations (from Area-1 to Area-2) is approximately 0.6% for a given load disturbance in the two area test system.

III. NEURAL NETWORKS BASED LOAD FREQUENCY CONTROL

3.1 Introduction:

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. The network function is determined largely by the connections between elements. Networks can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are trained, so that a particular input set leads to a specific target output set. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector.

Neural networks make use of a piece of information which is not used in conventional load frequency controllers, an estimate of the electric load perturbation (i.e. an estimate of the change in electric load when such a change occurs on the system) for training the network. This load perturbation estimate could be obtained by linear estimator, or by a nonlinear neural network estimator. In certain situations, it could also be measured directly from the bus. When a load estimate is available, the neural network achieves good dynamic response. This Section after giving the details of a multilayer feed forward neural network (MLFFNN), the load frequency control based on this artificial neural network is presented.

3.2 Multilayer feed- forward neural network:

The class of a feed-forward neural network distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons or hidden units. The function of hidden neurons is to intervene between the external input and the network output. By adding one or more hidden layers, the network is enabled to extract higher-order statistics. The source nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e. the first hidden layer). The output of the second layer is used as inputs to the third layer, and so on for the rest of the network.

The neurons in each layer of the network have as their inputs the output signals of the preceding layer. The set of output signals of the neurons in the output (final) layer of the network constitutes the overall response of the network to the activation pattern supplied by the source nodes in the input (first) layer.

The graph in Fig. 3.1 illustrates the layout of a multilayer feed-forward neural network for the case of a single hidden layer. The network in Fig. 3.1 is referred to as a 4-20-2 network because it has 4 source nodes, 20 hidden neurons, and 2 output neurons. The above network is fully connected in the sense that every node in each layer of the network is connected to every other node in the adjacent forward layer. If some of the communication links are missing from the network, then the network is partially connected.

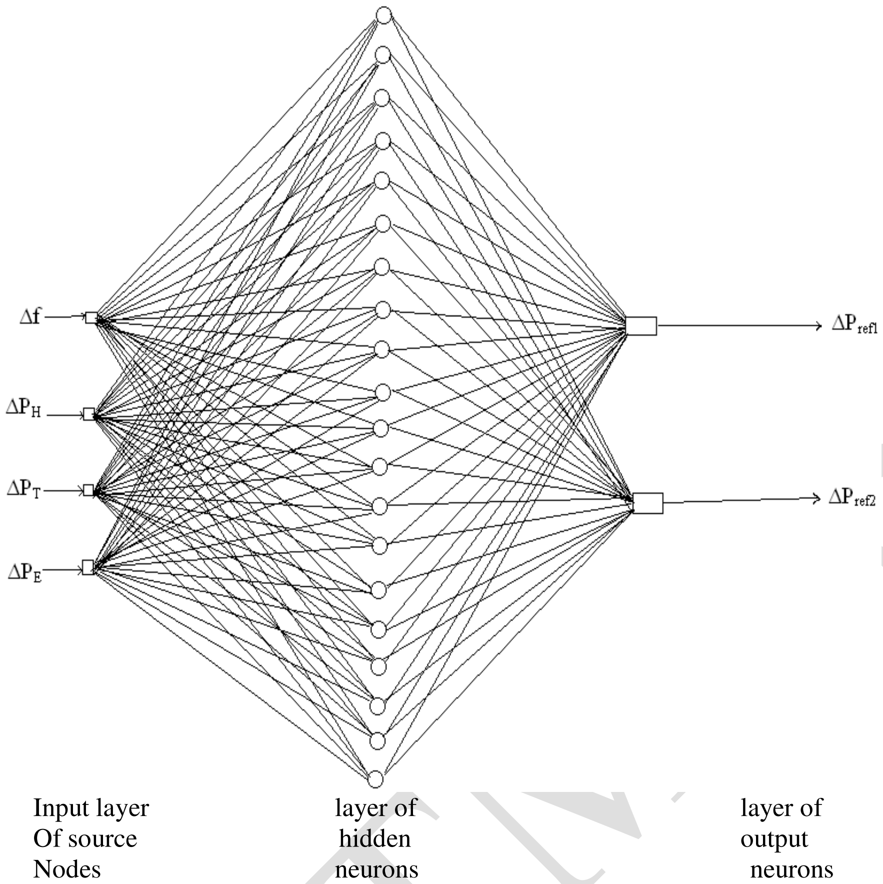

Fig 3.1 Proposed MLFFNN for LFC of two area system

3.3 Simulation results

The test system data is shown in Table 3.1. The block diagram of the ANN based load frequency control is shown in Fig. 3.6.1000 input-output patterns are sequentially generated for training the ANN for load frequency control. The training sets of the parameters are shown in Below.

Table 3.1 Parameter values for two area system

$K_{I,1}$ =.425	$K_{I,2}$ =.425
$K_{H,1}$ =0.1	$K_{H,2}$ =0.1
$T_{H,1}$=0.08	$T_{H,2}$=0.08
$K_{T,1}$ =1	$K_{T,2}$ =1
$T_{T,1}$ =0.3	$T_{T,2}$ =0.3
$K_{P,1}$ =1	$K_{P,2}$ =1
$T_{P,1}$ =19	$T_{P,2}$ =19
B_1=.425	B_2 =.425
R_1 =2.4	R_2 =2.4

The trained network is tested with the data and the results were practically matching. The simulation results of the ANN based load frequency control is compared against those obtained with conventional load frequency control in Fig 3.2 to Fig 3.4. The variations in frequency deviations in the two areas and the tie-line power deviations are obtained for a load deviation of 1%. It is observed that ANN based system are settling fast and frequency control is accurate than the response resulted in using PI based load frequency controller. Peak over shoots and time required to reach the steady state error value is less by approximately 2 seconds with ANN based load frequency control.

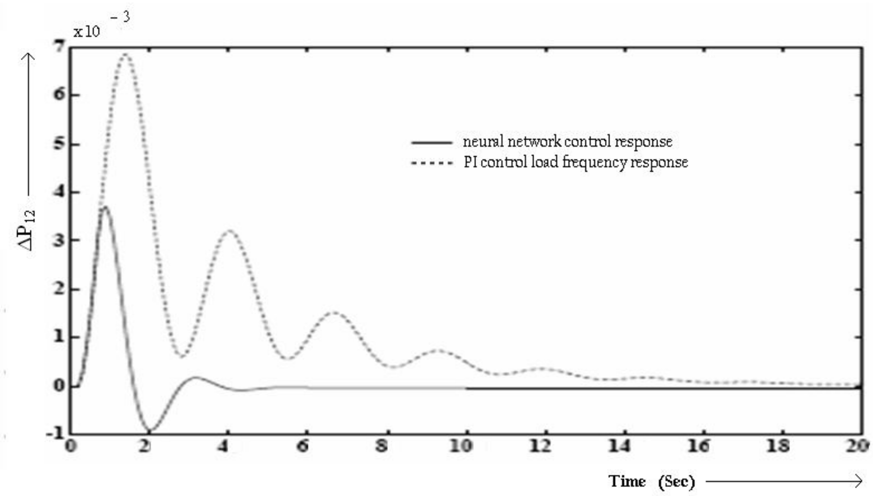

Fig 3.2 Tie line power variations

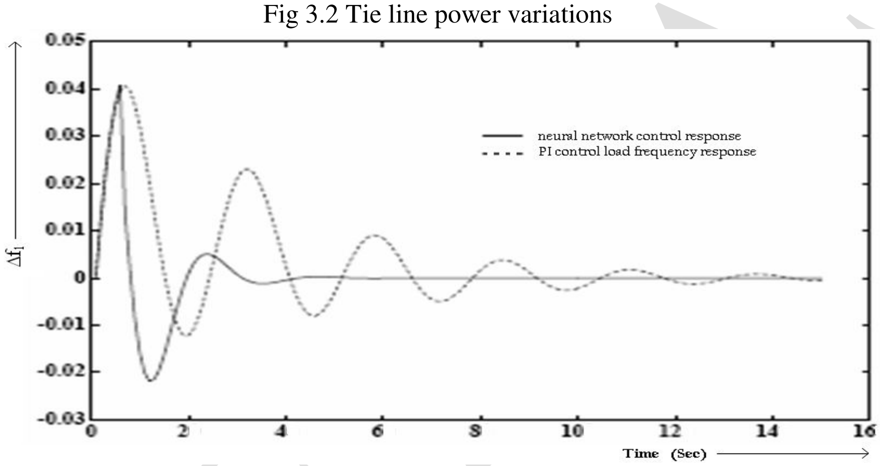

Fig 3.3 change in frequency Area-1

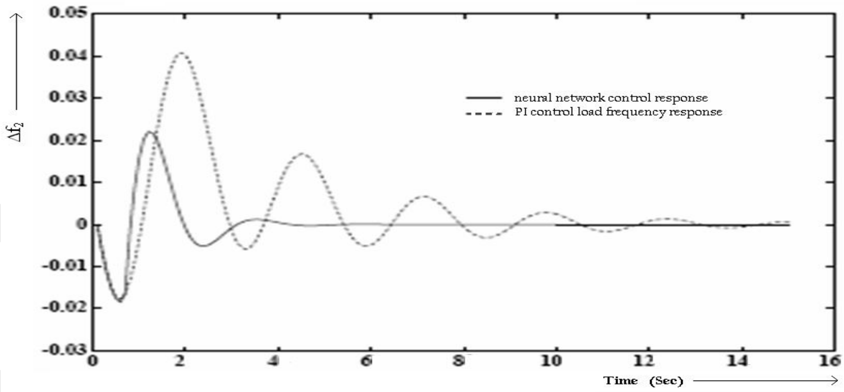

Fig 3.4 change in frequency in Area-2

IV. DYNAMIC NEURAL NETWORK BASED LOAD FREQUENCY CONTROL

4.1 Introduction

Dynamic neural units (DNUs), as the basic elements of dynamic neural networks, receive not only external inputs but also state feedback signals from themselves and other neurons. The synaptic connections in a DNU contain a self-recurrent connection that represents a weighted feedback signal of its state and lateral inhibition connections, which are the state feedback signals from other DNUs in the network. in terms of information processing, the feedback signals involved in a DNU deal with some processing of the past knowledge and store internal potential or internal state that is used to describe the dynamic characteristics of the network

4.2 Dynamic Neural Network based Load Frequency Control

A dynamic neural network model has unconstrained connectivity and has dynamical elements in its neuro processing units. The computational model for dynamic neural network is shown in Fig. 4.1. In general, there are l input signals which can be time-varying, n dynamic neuron units, n bias terms, and m output signals. The units have dynamics associated with them, and they receive input from themselves, bias term and from all other units. The output of a unit is a general sigmoid function of a state variable xi associated with the unit. The output of the overall network is a linear weighted sum of the unit outputs. The bias term bi is added to the unit inputs. DNNs described here can be contrasted with the mathematical representations of neural systems found in the literature . They take a popular form: standard algebraic neural network systems with external dynamics. The computational model of DNN is given in the following equations:

$$z_i = \sum_{j=1}^{n} q_{ij} y_j, \qquad i = 1,2,....,M \qquad [4.1]$$

$$y_i = \varphi_i(x_i), \qquad i = 1,2....,n \qquad [4.]$$

$$\varphi_i(x_i) = \frac{1}{1+e^{-(\gamma_i+\beta_i)}} \qquad [4.3]$$

$$\dot{x}_i = f_i(x_i, p) = \frac{1}{T_i}\left[-x_i + \sum_{j=1}^{n} w_{ij} y_j + \sum_{j=1}^{L} p_{ij} u_j + b_i\right] \quad ; \quad x_i(0) = x_{i0} \qquad i = \; 1,2...,n$$

Where γ_i and β_i are sigmoid nonlinearity parameters. The initial conditions on the state variables $x_i(0)$ must be specified. This model is similar to those in the literature . This model (DNN) approximates physical dynamic nonlinear systems, DNN converges to a periodic attractor or limit cycle. Problem of training trajectories by means of continuous recurrent neural networks whose feed- forward parts are multilayer perceptron. A set of parameters, initial conditions, and input trajectories, the set of Eqn. (4.2) and (4.3) can be numerically integrated from t = 0 to some desired final time tf. This will produce trajectories overtime for the state variables xi: We have used Runga–Kutta with 5-degree method, The integration step size has to be commensurate with the temporal scale of dynamics, determined by the time constants Ti: In our work, we have specified a lower bound on Ti and have used a fixed integration time step of some fraction (1/10) of this bound.

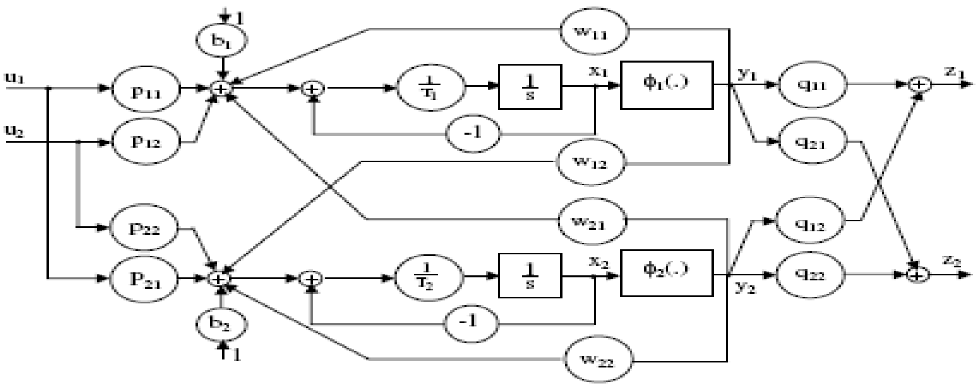

Fig.4.1 State diagram of two neurons and with two inputs/outputs

4.3 Simulation Results

The test system details i.e. time constant values and transfer function gain values of the system for DNN based load frequency control is detailed in appendix B and the equivalent dynamic neural network controller for Load Frequency Control is as shown in Fig. 4.2

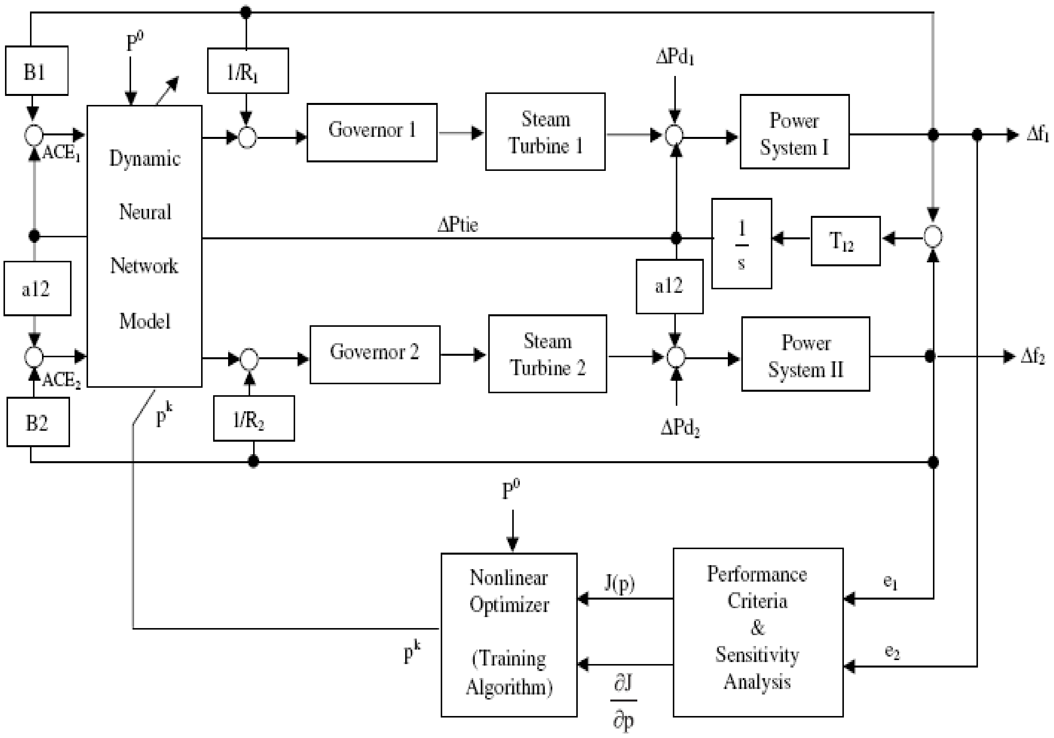

Fig 4.2 Simulink model for Dynamic neural network based load frequency control

The weight values obtained after training the dynamic neural network were given in Tables 4.1 to 4.4.

Table 4.1 Input weight values between ith and jth neuron

$P_{i \times j}$	1	2
1	10.18	10.325
2	0.0832	9.236

Table 4.2 Output connection weight values between ith and jth neuron

$Q_{i \times j}$	1	2
1	-45.445	-10.236
2	-3.0501	-0.145

Table 4.3 bias weight values in neuron 1 and 2

b_i	-
1	-28.436
2	-2.555

Table 4.4 Time constant values between ith and jth neuron

$T_{i \times j}$	1	2
1	0.199	0
2	0	0.4185

$$nonlinear \quad coefficients \quad of \quad the \quad sigmoid \quad function$$
$$\gamma_1 = 0.682, \qquad \gamma_2 = 2.846,$$

$$\beta_1 = -1.011, \qquad \beta_2 = -0.899,$$
$$initial \quad state \quad values$$
$$x(0) = [1.00 \quad -3.01]^T$$

In this project, application of several models to power systems for load frequency control has been proposed. It can be seen from the simulation results that the proposed controllers (DNN) cause less frequency drop and the oscillations in frequency damp out rapidly. It is also illustrated that the DNN based control approach shows better damping to the frequency variations following a load disturbance when compared to conventional and also the multilayer feedforward neural network based load frequency control.

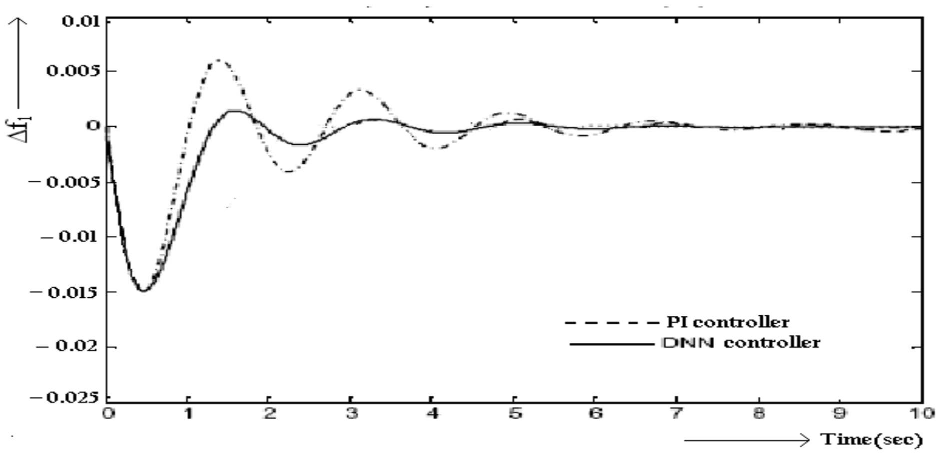

Fig 4.3 the frequency deviation of the first area for different controller types.

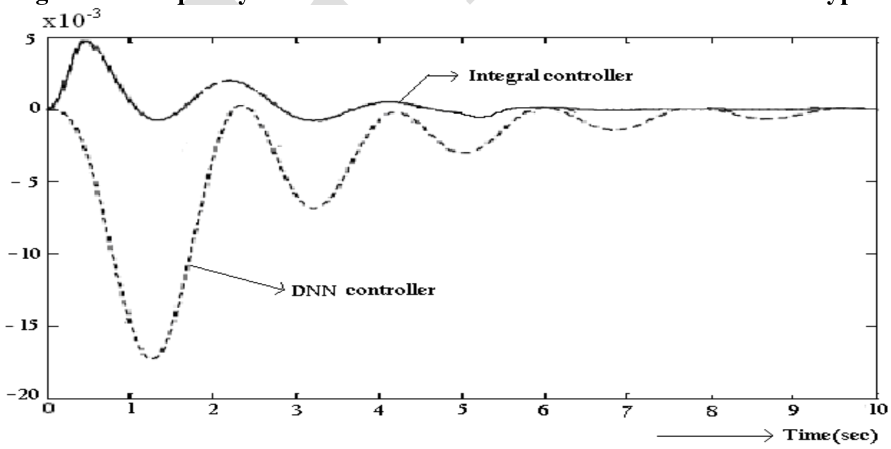

Fig 4.4 The frequency deviation of the second area for different controller types.

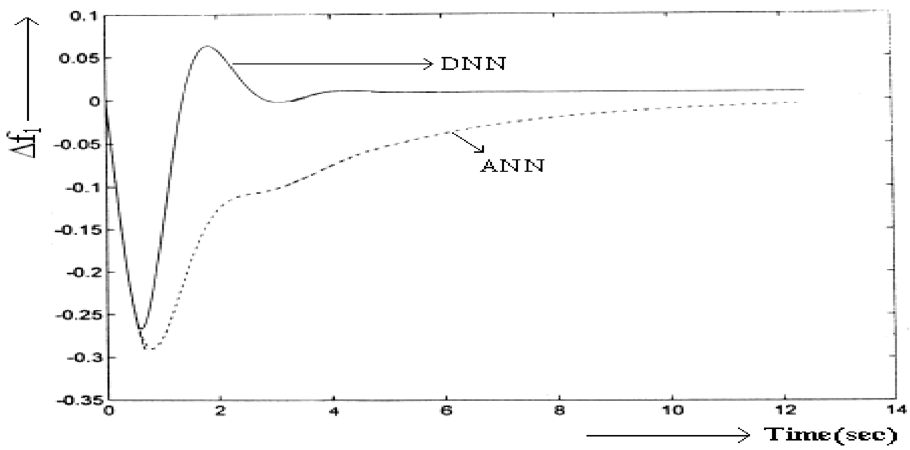

Fig 4.5 The frequency deviation of the first area for different controller types.

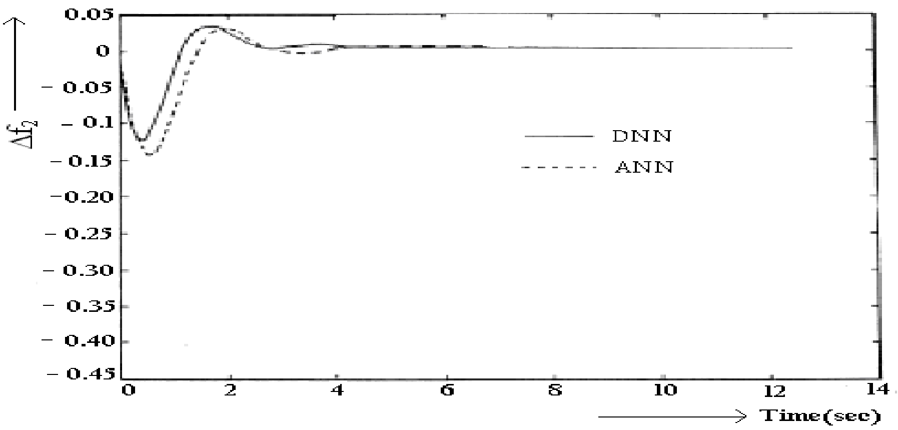

Fig 4.6 The frequency deviation of the second area.

V. CONCLUSION AND SCOPE FOR FUTURE WORK

5.1 CONCLUSION

In this work investigations related to the applications of multilayer feed forward network and dynamic neural network models that are applied to load frequency control of a two area system have been carried out. These investigations reveal that the ANN based control approach causes lesser frequency drop in the two areas than the conventional PI based LFC controllers. It has also been observed that the oscillations in frequency and tie line power following load disturbances damp out more rapidly in the case of ANN based LFC. Further the performance of DNN based LFC is seen to be better than that of MLFFNN based LFC.

5.2 SCOPE FOR FURTHER WORK

- Application of ANN based LFC to multi-area power systems.
- Investigations related to the hardware implementations

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